Non-redundant sampling for locally optimal* structures

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Overview



2 Concepts

Occomposition of Nussinov local minima





Introduction

• RNAs - structural diversity, usually important at a functional level

 Thermodynamic equilibrium (McCaskill, 1990): partition function
 → base-pairing probabilities within Boltzmann ensemble



- A Equilibrium assumption not always valid:
 - Riboswitches: 2 conformations with significant ΔG, both active yet difference unmitigated by sole presence/absence of ligand.
 - Co-transcriptional folding would not happen at equilibrium!
- Also, RNA degrades quickly MFE frequently not achieved

Importance of kinetic effects in formation of RNA structure Study RNA folding kinetics

RNA kinetics study

RNA kinetics analysis methods - 2 classes:

- Simulation methods (statistical) simulates RNA folding base by base/helix by helix
 - \rightarrow #trajectories required for reproducibility increases fast
- 4-step plan (approximative):
 - Sampling of representative set of structures
 - Assembling of representation of RNA folding landscape from samples
 - Estimation of transition rates between different parts of folding landscape representation
 - Investigation, notably evolution of concentrations during time
- sampling quality is essential, following steps depend on it:
- Missing functional structure > Losing part of RNA folding space
- Missing transitive structure Energy barrier overestimation



Diversity is problematic

- Suboptimal structures (Wuchty *et al.*, 1999)
 Combinatorial explosion
- Stochastic Sampling (Ding and Lawrence, 2003): Saturation
 High redundancy



(Kucharik et al., 2014)

- Most of sampling strategies: $P(sample) \propto e^{\frac{-E}{RT}}$
- Problem: oversampling of structures close to MFE

To overcome this problem:



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Concepts

Secondary structure (in this context):

Set of base pairs within an RNA sequence with following restictions

- Only pairs $\in \{\{C, G\}, \{A, U\}, \{G, U\}\}$ permitted
- No base triplets
- No pseudoknots



Orange and blue paths cannot coexist within the same structure

Locally optimal secondary structures

Local Minimum (LM) in RNA folding space



Local Minima (LM)

- Minimal free energy within neighborhood
- Neighbors of structure: All structures obtained by single base pair addition/removal

Energy model: Base pair maximization: RNANR \rightarrow Nussinov LMs... ... but also w.r.t. Turner model: RNAlocopt (WA. Lorenz *et al.*, 2011), RNAlocmin (Kucharik *et al.*, 2014) \rightarrow Turner LMs

structures

Flat structures

Beyond this point: min. helix length = 3 & stems of length 3 considered together

Nussinov model: Decomposition of secondary structures into flat structures, i.e. maximal by juxtaposition (Saffarian *et al.*, 2012):



Decomposition of local minima

Central idea:

- Generate all flat structures for RNA sequence (Saffarian et al., 2012)
- Find free energy E_f of each flat structure f (\approx loops in Turner model) \dots based on new interface to Vienna RNA package ¹
- Combine flat structures in any possible ways to obtain complete Nussinov local minima (while keeping track of free-energy)



Local optimality ensured by saturation of all flat structures Cannot add any new base pair without creating a conflict

How to sample Nussinov Local Minima?

¹Thanks Ronny!

Dynamic programming scheme for flat structure assembly



Partition function

$$\mathcal{Z} = \sum_{s \in \mathcal{S}} e^{rac{-E_s}{k_B T}}$$

S = space of secondary structures s E_s = energy of specific state s k_B = Arbitrary constant T = Absolute temperature

Here, S = Nussinov LMs secondary structures under structural restrictions



Space S of secondary structures of interest s

Secondary structure s of RNA sequence

$$\mathcal{Z}_s = \mathcal{Z}$$

 $P(s) = 1$



Space S of secondary structures of interest s



Secondary structure a of RNA sequence



Secondary structure a_1 of RNA sequence

$$P(a) = \frac{Z_a}{Z_s} = \frac{Z_a}{Z}$$

$$P(a_1) = \frac{Z_{a_1}}{Z_s} = \frac{Z_{a_1}}{Z}$$

$$\mathcal{A} \bigcap \mathcal{A}_1 = \emptyset$$

$$P(a) + P(a_1) < 1$$



Space \mathcal{A} of secondary structures a Space \mathcal{A}_1 of secondary structures a_1 $\mathcal{A} \subset \mathcal{S}, \ \mathcal{A}_1 \subset \mathcal{S}$



Secondary structure b of RNA sequence



Secondary structure b_1 of RNA sequence

 $P(b|a) = \frac{Z_b}{Z_a}, P(b_1|a) = \frac{Z_{b_1}}{Z_a}$ $\mathcal{B} \cap \mathcal{B}_1 = \emptyset, P(b) + P(b_1) < P(a)$ $P(b) = P(b|a).P(a) = \frac{Z_b}{Z_a} \cdot \frac{Z_a}{Z} = \frac{Z_b}{Z}$



Space \mathcal{B} of secondary structures bSpace \mathcal{B}_1 of secondary structures b_1 $\mathcal{B} \subset \mathcal{A} \subset \mathcal{S}, \ \mathcal{B}_1 \subset \mathcal{A} \subset \mathcal{S}$



Secondary structure c of RNA sequence

 $P(c|b) = \frac{\mathcal{Z}_b}{\mathcal{Z}_c}$

 $P(c) = P(c|b).P(b|a).P(a) = \frac{Z_c}{Z}$



Space C of secondary structures c $C \subset B \subset A \subset S$



• Problem: Avoid choosing sample after first selection

Solution : After generation of a given structure S, adjust probabilities of flat structures depending on their capacity to generate S again.So, how to adjust the probabilities?

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Efficient access to the probabilities of generated LMs through dedicated data structure (no complexity overhead... details on demand)

Results

Implementation - RNANR



- C implementation, based on Vienna package's RNAlib
- Non-redundant sampling, exhaustive enumeration, counting, expressive structural restrictions
- Availability:

https://project.inria.fr/rnalands/software/rnanr/

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Results

Structural Restrictions

- Space reduction using structural restrictions \rightarrow complexity reduction!
 - $\gamma ~ igwedge \Lambda$ Minimum helix length lpha, max #branches within multiloop γ
- Reminder: min helix length = 3
- Statistics on RNAStrand (Andronescu et al., 2006)



Exhaustive LMs enumeration

Test on SV11

- SV11 has active metastable (MS) state at 28.5 kcal.mol⁻¹ of MFE
- MS-like conformations unreachable for sampling algorithms
- Currently, numerical precision issues with non-redundant sampling \rightarrow Exhaustive enumeration in restricted folding space
- Structural restrictions: min. helix length = 4, max #branches within multiloop = 4

Results:

Comparison of Nussinov and Turner Local Minima

Method: Sampling Nussinov LMs + Gradient descent² \rightarrow Final structure, ie Turner Local Minimum

	Samples% avg (std.dev)	$\Delta\Delta G$ avg (std.dev)	Base pair dist. avg (std.dev)
Within search space	59.57% (21.00)	0.071 (0.309)	0.129 (0.289)
Global average	40.42% (21.00) 100.00% (-)	0.547 (0.925)	0.703 (0.757)

- More than half Nussinov LMs (52.4%) are also Turner LMs
- $\bullet~$ On average, a Nussinov LM is at ${\leq}0.55 \rm kcal.mol^{-1}$ and 0.7 base pairs to its closest Turner
- When the final structure is in the search space, Nussinov LMs are almost always Turner LMs (≈90%)

²Vienna package – Thanks Ronny and Gregor!

Theoretical speedup

T(K):#redundant structures to obtain K #unique structures Speed-up: T(K)/K = Avg #times a structure is (redundantly) sampled



Expected number of duplicitous samples per unique structure (A)

coverage

Practical speedup and complexity



Number of LMs returned

 No redundancy = faster coverage Comparison of speed of different software

• Limiting #branches within multiloop reduces complexity

Conclusion

New features

- Considerable speed up for the exploration of RNA folding landscapes
- Expressive structural restriction without added cost

Philosophical speedbump

- Exponential vs polynomial
- Non-redundant sampling can be easily implemented to any already existing sampling method
- Non-redundant sampling for statistical estimates: Does losing redundancy mean losing information?

In progress ... LOADING

- Numerical stability issues when Boltzmann factors become too low
- Validation of our local minima for kinetics analysis
- Non-redundant sampling for Turner model, χ scheduling...

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RNAlands project

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Non-redundant sampling

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